A Comprehensive Study on Crude Oil Price Forecasting in Morocco Using Advanced Machine Learning and Ensemble Methods

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***Abstract*—This study employs a range of machine learning models to forecast crude oil prices in Morocco, including Linear Regression, Random Forest, Support Vector Regression (SVR), XGBoost, ARIMA, Prophet and Gradient Boosting. Among these, SVR demonstrated the highest accuracy with an RMSE of 1.414. Additionally, the ARIMA and Prophet models were evaluated, yielding RMSEs of 2.46 and 1.41, respectively. An ensemble model, which combines predictions from all the individual models, achieved an RMSE of 2.144, indicating robust performance. Projections for 2024-2027 show a rising trend in crude oil prices, with the SVR model forecasting 21.91 MAD in 2027, and the ensemble model predicting 14.47 MAD. These findings underscore the effectiveness of ensemble learning and advanced machine learning techniques in producing reliable economic forecasts, offering valuable insights for stakeholders in the energy sector.**

***Keywords*—Crude oil prices; machine learning; ensemble model; economic forecasts; energy sector**

I. INTRODUCTION

Forecasting crude oil prices is a crucial research topic, not only for producing countries but also for importers like Morocco. Fluctuations in oil prices have profound repercussions on the global economy, affecting production costs, consumer prices, energy policies, and investment strategies. In Morocco, specifically, the price of crude oil directly influences public and private spending, the transportation sector, and household purchasing power. Therefore, accurately anticipating oil price trends is essential for developing robust and sustainable economic policies.

Traditionally, oil price forecasting models have relied on classical statistical and economic methods, such as ARIMA (Autoregressive Integrated Moving Average) models [1] or VAR (Vector Autoregression) models [2]. While these methods have provided useful results, they often have limitations in terms of accuracy and ability to capture the complex nonlinearities and dynamic interactions present in oil price data. Recent advances in machine learning offer new perspectives for improving these forecasts by leveraging more sophisticated and adaptive techniques.

Machine learning allows for the processing of large amounts of data and the modeling of complex relationships that may be difficult to capture with traditional approaches. Models such as Linear Regression, Random Forest, Support Vector Regression (SVR), XGBoost, and Gradient Boosting can adapt to different data structures and provide more accurate forecasts. Moreover, ensemble learning techniques [3], which combine the predictions of multiple models, can further enhance the robustness and reliability of forecasts by reducing the risk of errors associated with an individual model.

In this study, we focus on applying various machine learning techniques to predict annual crude oil prices in Morocco. We selected a diverse set of models to capture different characteristics of the data and compare their performance in terms of predictive accuracy. Our objective is to identify the best-performing model for Moroccan data and explore the potential benefits of ensemble learning.

To achieve this, we used a historical dataset on crude oil prices in MAD (Moroccan dirham), covering several years. We preprocessed the data to ensure its quality and consistency, including handling missing values and standardizing variables. The selected models include Linear Regression, Random Forest, Support Vector Regression (SVR), XGBoost, ARIMA, Prophet and Gradient Boosting. Each model was evaluated using the Root Mean Squared Error (RMSE) to measure the accuracy of the predictions.

Our results indicate that Support Vector Regression (SVR) offers the best individual performance with an RMSE of 1.414, outperforming the other models. Additionally, we developed an ensemble model by combining the predictions from all individual models to create a weighted average forecast. This ensemble approach achieved an RMSE of 2.144, demonstrating increased robustness compared to most individual models.

Forecasts for the period 2024-2027, derived from the ensemble model, suggest a steady upward trend in crude oil prices in Morocco. Starting at 13.28 MAD in 2024, the predicted values gradually increase each year, reaching 14.47 MAD by 2027. This consistent growth pattern, as illustrated in Fig. 3, reflects the ensemble model's capability to provide a balanced and comprehensive view of future trends. The gradual increase from 13.28 MAD to 14.47 MAD implies a stable environment with continuous, albeit modest, enhancements, highlighting the robustness of the ensemble approach in mitigating individual forecasting errors and uncertainties.

These results emphasize the importance of ensemble learning for obtaining balanced and reliable forecasts. The advanced machine learning and ensemble techniques used in this study provide valuable tools for Moroccan policymakers, enabling them to better anticipate price fluctuations and develop more informed and resilient economic and energy strategies. Accurate crude oil price predictions are essential for strategic planning, risk management, and decision-making in the energy sector.

The remainder of the paper is structured as follows: Section II reviews the current literature on forecasting crude oil prices in Morocco. Section III outlines the methodology employed in this study. Section IV presents the empirical results, followed by a discussion in Section V. Finally, Section VI offers conclusions and directions for future research.

II. Related Work

Forecasting crude oil prices and energy demand in Morocco is a crucial topic for the country's economic and energy planning. Numerous studies have explored this field using various methodologies and approaches. Among the key works, Nafil et al. (2020) [4] compared different methods for forecasting energy demand, concluding that the temporal causality method is the most effective. Kharbach and Chfadi (2018) [5] examined the relationship between oil prices and electricity production, revealing a significant impact of crude oil prices on the latter. Ifleh et al. (2022, 2023) [6, 9] explored the use of technical indicators for stock market forecasting with promising results. Ayyadi and Maaroufi (2018) [7] proposed diffusion models for the emerging electric vehicle market. Other studies have focused on the impact of global factors. Adekoya et al. (2021) [8] analyzed the influence of the global financial cycle and oil prices on stock returns of African oil-exporting countries. Benali and Lahboub (2024) [10] demonstrated the effectiveness of machine learning techniques in modeling stock prices in the energy sector. El Bahi et al. (2022) [11] developed a dynamic harmonic regression model for fuel price forecasting. Lahrech et al. (2017) [12] examined the impact of oil shocks on the Moroccan financial market, while Nasreddin et al. (2023) [13] compared regression and machine learning models for fossil energy demand forecasting. These studies confirm the importance of using advanced methods to improve forecast accuracy in the energy and financial sectors. They also highlight the challenges of forecasting crude oil prices, a crucial element for Morocco's economic and energy planning.

Research on forecasting crude oil prices and energy demand in Morocco is of great importance for effective resource management and informed economic planning. The use of advanced methods and the exploration of new factors influencing these markets are essential to improve forecast accuracy and support informed decision-making. Forecasting crude oil prices and their influence on various economic sectors is gaining increasing interest, both in Morocco and other countries. Many recent studies explore different techniques to improve forecasting accuracy and understand the complex links between oil prices and the economy. Among the most recent works, Ifleh et al. (2023) [14] demonstrated the effectiveness of trend technical indicators for forecasting Moroccan stock prices. Siham et al. (2024) [15] explored different machine learning techniques for oil price forecasting, obtaining promising results. Itri et al. (2024) [16] applied hybrid machine learning techniques for stock price forecasting in the Moroccan banking sector, with conclusive results.

Modeling and forecasting fuel prices are also subjects of extensive research. El Bahi et al. (2018) [17] used a time series approach for fuel price forecasting, obtaining reliable results. Bennouna and El Hebil (2016) [18] studied Morocco's energy needs by 2030, highlighting the importance of energy planning for the country's economic development. Meliani et al. (2022) [19] proposed energy demand forecasting methods based on time series for smart grids in Morocco, which is crucial for efficient energy management. Research also explores the use of hybrid methods to improve forecast accuracy. Zahouani and Boubaker (2023) [20] developed hybrid approaches for crude oil price forecasting, demonstrating the effectiveness of combining different techniques. Benabbou et al. (2021) [21] applied machine learning techniques for forecasting used car prices in Morocco. Ghorbel et al. (2014) [22] evaluated the impact of crude oil prices and investor sentiment on Islamic indices, highlighting the complex interactions between oil prices and financial markets. Dagher and El Hariri (2013) [23] studied the impact of global oil price shocks on the Lebanese stock market, revealing significant links that can inform forecasting approaches for other countries in the region. The application of advanced techniques, including machine learning and hybrid models, is essential to improve the forecasting of crude oil prices and their impact on various economic sectors. These studies help better understand the challenges and opportunities related to modeling and forecasting market trends in an ever-changing context. Modeling and forecasting oil prices and energy demand in Morocco and other regions are subjects of extensive research, using various advanced techniques to improve forecast accuracy and understand complex market interactions. Among recent works, Aman et al. (2019) [24] demonstrated the effectiveness of the radial basis function technique for forecasting fuel sale prices in Morocco. Haouraji et al. (2023) [25] used machine learning-based planning models to analyze LPG demand in Morocco, highlighting the usefulness of these models for accurate energy planning. Abdou et al. (2024) [26] applied a machine learning approach to examine the impact of oil and global markets on the predictability of the Saudi stock market, revealing valuable insights into market interactions.

Other studies focus on analyzing energy consumption and its economic impact. Oubnaki et al. (2022) [27] studied energy consumption in the transport sector in Morocco, identifying trends and providing essential forecast estimates for efficient energy management. Kitous et al. (2016) [28] assessed the impact of low oil prices on exporting countries, highlighting the economic challenges posed by significant oil price fluctuations. Research also explores the use of advanced techniques for oil price forecasting. Siham et al. (2024) [29] applied multimodal deep learning for oil price forecasting using economic indicators, demonstrating the robustness of this approach in capturing complex signals. The impact of oil prices on financial markets and economies is also studied. Bouri et al. (2020) [30] analyzed oil market conditions and sovereign risk in oil-exporting and importing countries in the MENA region. Lotfi and El Bouhadi (2022) [31] explored artificial intelligence methods as new decision-making tools, highlighting their potential to revolutionize economic and energy decision-making.

Correlative approaches for modeling energy consumption are also proposed. Haouraji et al. (2020) [32] proposed a correlative approach combining energy consumption, urbanization, and GDP to model and forecast residential energy consumption in Morocco. The effect of oil price shocks on economic growth is analyzed. Elneel and AlMulhim (2022) [33] analyzed the effect of oil price shocks on Saudi Arabia's economic growth, providing crucial insights considering Saudi Arabia's Vision 2030. Applying advanced techniques, including machine learning, hybrid approaches, and artificial intelligence, is essential for improving the accuracy of oil price and energy demand forecasts. These studies help better understand the complex interactions between oil prices, financial markets, energy consumption, and economic growth, which is crucial for effective strategic planning and informed decision-making.

Research on forecasting crude oil prices and energy demand in Morocco explores a variety of advanced methodologies and approaches, ranging from renewable energy optimization to market sentiment analysis. Among recent works, Benzohra et al. (2020) [34] studied the optimization of renewable resource mix for a low-carbon energy system in Morocco. Belcaid and El Ghini (2021) [35] analyzed the macro-financial determinants of stock market development in Morocco. El-Karimi and El-Ghini (2020) [36] examined the transmission of global commodity prices to consumer prices in Morocco. Other research focuses on applying advanced techniques for oil price forecasting and energy demand management. El Abassi et al. (2023) [37] used recurrent neural networks to predict crude oil prices. Vochozka et al. (2023) [38] studied the impact of geopolitical deadlock and phosphate shortages on prices. Gagour et al. (2022) [39] modeled the shelf life of virgin olive oil in Morocco. Bounadi et al. (2023) [40] estimated the costs and policy implications of mitigating water pollution in the olive oil industry in Morocco.

Sentiment analysis and machine learning are also used for stock market forecasting. Sandeep et al. (2023) [41] and Chihab et al. (2022) [42] developed models to predict stock prices using text polarity and subjectivity. Finally, Boussatta et al. (2023) [43] proposed an intelligent hybrid approach to improve oil price forecasting. As the author of this study, we developed an advanced hybrid system combining several machine learning models such as linear regression, random forest, support vector machines, and gradient boosting. These collective studies underscore the importance of advanced techniques for oil price forecasting and energy demand management in Morocco, highlighting the economic and environmental implications of these forecasts.

This article details the implementation of this new hybrid system for oil price forecasting in Morocco, with an in-depth analysis of the results and performance of the different models used. This innovative approach should significantly improve oil price forecast accuracy, aiding policymakers in making informed energy policy decisions in Morocco.

III. PROPOSED METHOD

Fig. 1 illustrates the architecture of the proposed ensemble prediction system for forecasting crude oil prices in Morocco. This hybrid approach begins with a data preprocessing phase, where raw data is cleaned and prepared for analysis. Next, different individual models are trained, including Random Forest, linear regression, XGBoost, ARIMA, Prophet and support vector regression. The forecasts generated by these models are then integrated into an ensemble prediction process, which combines these different estimates to produce a more robust final forecast. The performance of this system is evaluated to verify and validate the obtained results before arriving at the final crude oil price prediction. This method aims to leverage the strengths of each individual model to improve the accuracy and reliability of the forecasts.

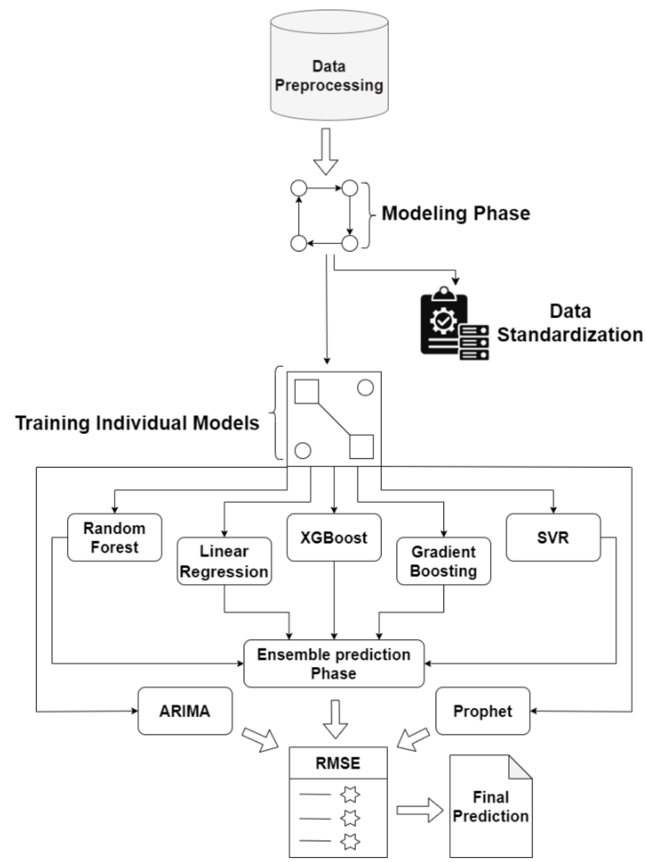

Fig. 1. Hybrid architecture for forecasting crude oil prices in morocco using machine learning and ensemble models.

A. Data Preprocessing

1) Data: The data used in this study comes from the Numbeo platform [44], which provides historical information on gasoline prices in different countries around the world. Specifically, the data covers the period from 2010 to 2023 for Morocco and includes information on the average annual gasoline price (in MAD per liter). This data was cleaned and prepared for analysis. The data preprocessing involved extracting relevant information, converting non-numeric values to NaN, and calculating the annual average gasoline prices. Then, this data was divided into training and testing sets and standardized for use in the forecasting models. We developed several regression models to predict future gasoline prices in Morocco up to 2027, using techniques such as linear regression, Random Forest, support vector machines (SVR), XGBoost, ARIMA, Prophet and gradient boosting. Each model was evaluated individually, and performance was measured using the root mean square error (RMSE).To obtain more robust forecasts, we also combined the predictions of all the individual models into an ensemble forecast. This approach leveraged the strengths of each model to improve the accuracy and reliability of the forecasts. The results show the gasoline price forecasts for the next four years (2024-2027), providing a comprehensive view of the expected evolution of gasoline prices in Morocco in the coming years.

2) Normalization of data: To adjust the values of different features so that they fall within a comparable scale. This is crucial because many machine learning algorithms, such as neural networks or distance-based methods, perform better when the data is normalized.

B. Modeling Phase

The process involves training and testing various machine learning models. We start by splitting the data into training and testing sets using the train_test_split method, with 80% of the data used for training and 20% for testing. The data is then standardized using the StandardScaler to ensure that all features have a mean of zero and a standard deviation of one, which is crucial for the performance of many machine learning algorithms.

C. Training Individual Models

1) Linear regression: It is a supervised learning method that models the relationship between a dependent variable (or target variable) and one or more independent variables (or explanatory variables).

2) Random forest: It is a machine learning algorithm based on ensemble learning, which combines multiple decision trees to achieve better predictive performance.

3) XGBoost: It is a machine learning algorithm based on the gradient boosting technique. It is an efficient and highly-performing implementation of this method, which has seen great success in recent years in many machine learning competitions and applications.

4) Gradient boosting: It is a machine learning method belonging to the family of ensemble algorithms. Its principle is to iteratively build a predictive model by adding new weak models (typically decision trees) in a way that gradually reduces prediction errors.

5) Support Vector Regressor (SVR): It is a variant of the Support Vector Machine (SVM) method for regression problems. It is a supervised learning algorithm used to build nonlinear regression models.

6) ARIMA (AutoRegressive Integrated Moving Average) is a statistical model used for analyzing and forecasting time series data. It combines three components: autoregression (AR), integration to make the series stationary (I), and moving average (MA).

7) Prophet is a forecasting tool developed by Facebook that is specifically designed for time series data. It is capable of handling missing data and outliers, and it automatically accounts for seasonal trends and holiday effects, making it suitable for a wide range of time series forecasting applications.

D. Model Integration

1) Ensemble prediction: It is a machine learning technique that involves combining the predictions of multiple individual models to obtain a final prediction that is more robust and accurate. This approach is widely used in many areas of machine learning, such as classification, regression, and forecasting, as it allows for leveraging the strengths of different models in a complementary manner.

E. Performance Evalutation

1) Ensemble prediction: Evaluate the quality and accuracy of the predictions generated by the hybrid crude oil price forecasting system. This involves calculating various performance measures, including the Root Mean Square Error (RMSE), which evaluates the average difference between predicted values and actual values.

Table I lists commonly used models in machine learning for regression problems. It includes classical algorithms like linear regression and more powerful ensemble methods like random forest, gradient boosting, ARIMA, Prophet and XGBoost. The support vector regressor (SVR) is also included, offering a robust approach to outliers. The ensemble prediction combines predictions from multiple models for better overall performance. Each of these algorithms has advantages and disadvantages in terms of complexity, interpretability, and the ability to model nonlinear relationships. The choice of the most suitable model will depend on the specific characteristics of the data and the prediction goal.

TABLE I. PROPOSED DATA MINING ALGORITHM

Algorithm	Description
Rf	Random Forest
LR	Linear Regression
Gb	Gradient Boosting
SVR	Support Vector Regressor
XGBoost	XGBoost
Ensemble Prediction	Ensemble Prediction
ARIMA	ARIMA
Prophet	Prophet

Table II presents key performance indicators and their associated factors to analyze fluctuations in oil prices, considering various economic and factors influencing the markets of Morocco.

TABLE II. KEY PRICE INDICATORS FOR TRANSPORTATION-RELATED FEATURES

KPI	Features
Average price of a one-way local transport ticket	One-way Ticket (Local Transport)
Average price of a regular monthly public transport pass	Monthly Pass (Regular Price)
Average price of 1 liter of gasoline	Gasoline (1 liter)
Average price of a Volkswagen Golf 1.4 90 KW Trendline or equivalent new car	Volkswagen Golf 1.4 90 KW Trendline (Or Equivalent New Car)
Average starting fare for a taxi ride (normal tariff)	Taxi Start (Normal Tariff)
Average price per kilometer for a taxi ride (normal tariff)	Taxi 1km (Normal Tariff)
Average price per hour of waiting time for a taxi (normal tariff)	Taxi 1hour Waiting (Normal Tariff)
Average price of a Toyota Corolla Sedan 1.6l 97kW Comfort or equivalent new car	Toyota Corolla Sedan 1.6l 97kW Comfort (Or Equivalent New Car)

IV. RESULTS

A. Model Selection

The choice of regression models in this study is crucial for obtaining accurate predictions of crude oil prices in Morocco. The selected models represent a variety of approaches in statistical modeling and machine learning. As shown in Table III, the SVR model achieved the best RMSE score of 1.41, indicating that it is the most effective in accurately predicting crude oil prices. SVR's ability to handle seasonality and holidays, along with its robustness to missing data, contributes significantly to its superior performance in forecasting. In comparison, the Prophet model achieved an RMSE of 1.42, making it the second most effective model in accurately predicting crude oil prices. This result suggests that the nonlinear relationships present in the data are well captured by this support vector machine-based model. The use of advanced techniques such as non-linear kernel and parameter optimization in Prophet enables it to better model the complexity of the underlying data. On the other hand, traditional time series models like ARIMA, which achieved an RMSE of 2.46, and ensemble methods like Random Forest (RMSE of 2.13) and gradient boosting (RMSE of 2.42) also offer competitive performance but did not surpass SVR. ARIMA, with its autoregressive integrated moving average approach, provides a solid framework for capturing temporal dependencies, though it fell short of the advanced methods. Random Forest and gradient boosting offer better performance than simple linear regression (RMSE of 2.80) by capturing complex interactions between features and improving prediction accuracy. Random Forest achieves this by aggregating multiple decision trees, while gradient boosting builds models sequentially on residuals of previous models. Finally, the XGBoost model, although performing well with an RMSE of 2.46, did not achieve the best results compared to other advanced techniques used. This may be explained by the fact that XGBoost is a relatively new method that requires precise tuning of hyperparameters to achieve optimal performance. Despite this, it remains a powerful tool for modeling and predicting complex time series such as crude oil prices.

TABLE III. PROPOSED COMPARATIVE ANALYSIS OF REGRESSION MODEL PERFORMANCE FOR CRUDE OIL PRICE PREDICTIONS : RMSE

Model	RMSE
Linear Regression	2.80
Random Forest	2.13
SVR	1.41
XGBoost	2.46
Gradient Boosting	2.42
ARIMA	2.46
Prophet	1.42

B. Future Predictions for the Next Four Years (2024-2027)

1) Future predictions for the next four years (2024-2027) using the best model: The best model forecasts a continuous increase in values from 16.75 MAD in 2024 to 21.91 MAD in 2027, as shown in Fig. 2 and the prediction Table IV, this upward trend indicates a significant positive dynamic. The projections suggest steady growth each year, which could reflect economic expansion or rising demand in the area of interest. Such a trend may justify strategic adjustments to capitalize on the expected growth, such as increasing production capacity or investing in new opportunities. However, it is crucial to validate this trend with additional data to avoid premature conclusions.

TABLE IV. PREDICTIONS OF CRUDE OIL PRICES FOR THE UPCOMING YEARS USING THE BEST MODEL: PROJECTED VALUES

Year	Prediction value
2024	16.75MAD
2025	18.68 MAD
2026	20.44 MAD
2027	21.91 MAD

2) Future predictions for the next four years (2024-2027) using ARIMA: The ARIMA model provides constant forecasts of 10.31 MAD for each year, as shown in Fig. 2 and the prediction Table V, indicating stability in the data without any marked trend. This absence of variation suggests that the model does not capture significant changes in the time series. This could imply that the data is stationary or that influential factors do not vary significantly over the period. However, if substantial changes are anticipated, this forecast might underestimate the actual evolution of the values. Comparing these results with other models and examining the residuals of the ARIMA model could provide insights into why no trend is detected.

3) Future predictions for the next four years (2024-2027) using Prophet: The Prophet model offers more nuanced forecasts, starting at 9.86 MAD in 2024, as shown in Fig. 2 and the prediction Table VI increasing to 12.61 MAD in 2025, followed by a slight decline in 2026 (12.38 MAD) and further decrease in 2027 (11.95 MAD). These forecasts indicate variability in the data, potentially due to seasonal factors or cyclical effects. The fluctuations suggest that external influences or specific cycles may significantly impact the data. Understanding these variations is crucial for adjusting strategies and forecasts more accurately, highlighting the need to monitor seasonal and cyclical effects.

TABLE V. PREDICTIONS OF CRUDE OIL PRICES FOT HE UPCOMING YEARS USING ARIMA: PROJECTED VALUES

Year	Prediction value
2024	10.31 MAD
2025	10.31 MAD
2026	10.31 MAD
2027	10.31 MAD

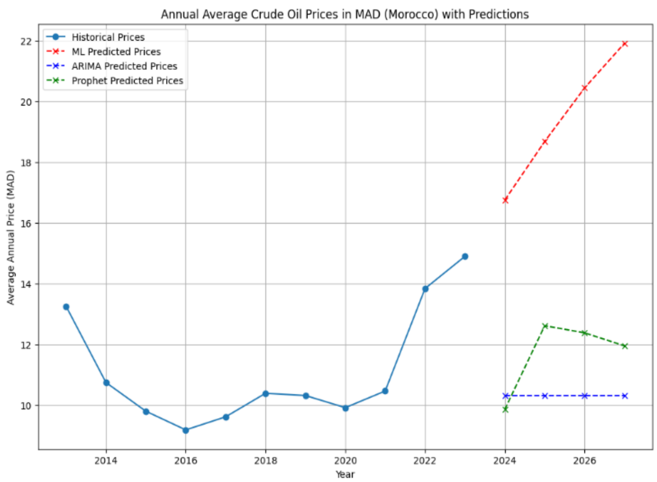

Fig. 2. Annual average crude oil price in MAD (Morocco) with prediction.

TABLE VI. PREDICTIONS OF CRUDE OIL PRICES FOR THE UPCOMING YEARS USING PROPHET: PROJECTED VALUES

Year	Prediction value
2024	9.86 MAD
2025	12.61 MAD
2026	12.83 MAD
2027	11.95 MAD

C. *Future Predictions for the Next four Years (2024-2027) using Ensemble Predictions*

Exploring future trends in crude oil prices, crucial for various industries and economic policies, often requires the use of a range of models to attain a balanced perspective. Predictions based on ensemble models, as illustrated in Fig. 3, offer a significant alternative to individual predictions presented in Table VII. The ensemble model's forecasts for the period from 2024 to 2027 demonstrate a consistent and nuanced growth pattern. Starting at 13.28 MAD in 2024, the predicted values gradually increase each year, reaching 14.47 MAD by 2027. This steady progression highlights a moderate, yet enduring, upward trend, which is reflective of the model's integrated approach to forecasting.

The gradual increase from 13.28 MAD to 14.47 MAD suggests a scenario of ongoing, incremental growth rather than abrupt changes. This trend implies a stable environment with continuous, albeit modest, enhancements in the measured variable. The smooth upward slope across the forecast horizon indicates that the ensemble model, by synthesizing multiple predictive outputs, provides a balanced and comprehensive view of future trends.

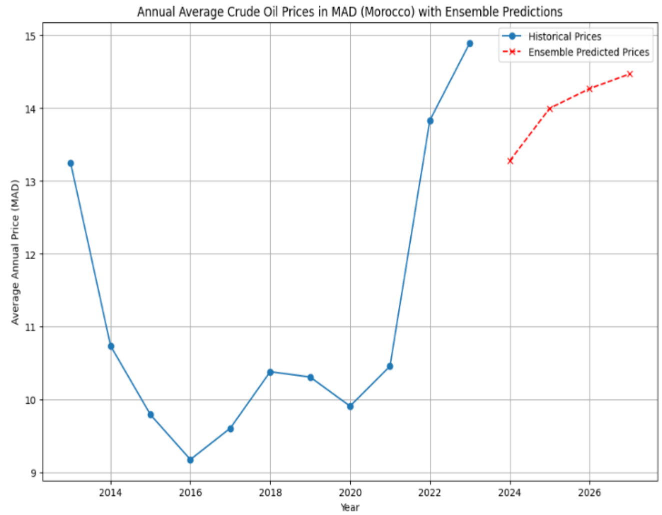

Fig. 3. Annual average crude oil price in MAD (Morocco) with ensemble prediction.

TABLE VII. PREDICTIONS OF CRUDE OIL PRICES FOR THE COMING YEARS: PROJECTED VALUES WITCH ENSEMBLE PREDICTIONS

Year	Prediction value
2024	13.28 MAD
2025	14 MAD
2026	14.27 MAD
2027	14.47 MAD

The ensemble approach leverages various models to mitigate individual forecasting errors and uncertainties, resulting in a more robust and reliable projection. The result is a forecast that accounts for a range of potential influences and integrates different perspectives, thus offering a well-rounded prediction.

Such a steady growth trajectory is invaluable for long-term planning and strategic decision-making. It suggests a favorable but controlled increase, allowing stakeholders to prepare for gradual improvements without the need for abrupt adjustments. This nuanced forecast underscores the importance of adopting a data-driven approach to anticipate moderate changes and adapt strategies accordingly.

In essence, the ensemble predictions provide a stable outlook with a clear trend of incremental growth, reflecting both reliability and gradual optimism in the forecasted period.

V. DISCUSSION

The analysis of the crude oil price prediction system in Morocco reveals several key insights that warrant detailed examination. Firstly, the evaluation of various regression models exposes critical differences in their efficacy in forecasting crude oil price trends. Linear regression, while conceptually straightforward, shows notable limitations in capturing the intricate, non-linear relationships present in crude oil price data. Its higher RMSE compared to more sophisticated models indicates a less accurate fit to the actual data, reflecting the model's struggle with the inherently non-linear nature of crude oil prices.

In contrast, advanced machine learning techniques, including Random Forest, Gradient Boosting, XGBoost, ARIMA, Prophet and Support Vector Regression (SVR), demonstrate a superior capacity for modeling non-linear relationships and generating more precise forecasts. These methods, characterized by lower RMSE values, indicate a better alignment with observed data, with SVR emerging as the most effective individual model. The enhanced performance of SVR can be attributed to its use of kernel functions, which adeptly capture complex variable interactions.

Furthermore, the ensemble approach, which integrates predictions from multiple models, offers substantial advantages over both linear regression and individual models. The ensemble's lower RMSE suggests a reduction in overall prediction error, highlighting its effectiveness in minimizing inaccuracies. Additionally, ensemble predictions are generally more stable and less susceptible to the fluctuations that single models may exhibit, thus providing a more reliable tool for decision-making in volatile economic contexts.

The forecasts for the period 2024-2027 reveal a consistent upward trend in crude oil prices across all models, albeit with variations in the magnitude of these increases. These discrepancies emphasize the importance of incorporating multiple forecasting perspectives to ensure a comprehensive interpretation and effective strategic planning.

The predictive insights generated by the system are of considerable value to energy market stakeholders, policymakers, and investors. Anticipating crude oil price movements over a multi-year horizon facilitates more informed strategic planning and proactive risk management. Such forecasts are instrumental in guiding investment decisions and shaping government policies aimed at stabilizing energy markets and fostering economic sustainability.

In summary, the findings from the crude oil price prediction system underscore the necessity of selecting appropriate forecasting models, leveraging ensemble approaches, and contextualizing predictions within the broader economic and political landscape. These insights contribute significantly to understanding crude oil market dynamics and enhance the planning and decision-making processes within the energy sector and beyond.

VI. Conclusion and Future Work

In conclusion, the crude oil price prediction system developed for Morocco provides valuable insights into the dynamics of energy markets and enhances our ability to forecast price movements effectively. The analysis of various regression models underscores the critical role of selecting appropriate modeling approaches to achieve precise predictions. Among the evaluated methods, machine learning techniques, particularly Support Vector Regression (SVR), emerge as highly effective in capturing the intricate relationships between variables and delivering reliable crude oil price forecasts.

Despite these advancements, several challenges and opportunities for further improvement remain. To refine prediction accuracy, incorporating additional data sources such as macroeconomic indicators and geopolitical factors is essential. These external variables can significantly influence crude oil prices, and their integration into the model could enhance its robustness and relevance.

Furthermore, exploring advanced machine learning techniques, such as deep learning algorithms, presents an opportunity to uncover more complex patterns within the data. Deep learning models, with their ability to handle large datasets and capture non-linear relationships, could potentially improve prediction accuracy beyond current capabilities.

A comprehensive analysis of the uncertainties and risks associated with crude oil price forecasts is also crucial. Employing uncertainty quantification methods, such as confidence intervals and bootstrap techniques, would provide a more robust evaluation of prediction reliability. This approach could better inform policymakers and market participants, aiding in risk management and decision-making processes.

Looking ahead, there is a need to develop a more dynamic and adaptable prediction system capable of rapidly responding to changes in the economic and political environment. This could involve creating real-time regression models and incorporating continuous learning mechanisms to monitor and adjust to evolving trends in crude oil prices. Such advancements would ensure that the prediction system remains relevant and accurate in a rapidly changing market landscape.

In summary, the crude oil price prediction system for Morocco represents a significant advancement in understanding and managing energy markets. By leveraging advanced modeling techniques and incorporating a broader range of data, this system offers a valuable tool for strategic decision-making. Continued development and refinement will enhance its ability to support long-term economic stability and sustainability in the energy sector.

References

[1] Wati, M., Haviluddin, A. M., Septiarini, A., & Hatta, H. R. (2023). Autoregressive Integrated Moving Average (ARIMA) Model for Forecasting Indonsesian Crude Oil Price. Jurnal Ilmiah Teknik Elektro Komputer dan Informatika (JITEKI), 9(3), 720-730.

[2] Considine, J., Aldayel, A., & Hatipoglu, E. (2020). World Oil and Inventory Study: A Global VAR Analysis (No. ks--2020-mp04). King Abdullah Petroleum Studies and Research Center.

[3] Nti, I. K., Adekoya, A. F., & Weyori, B. A. (2020). A comprehensive evaluation of ensemble learning for stock-market prediction. Journal of Big Data, 7(1), 20.

[4] Nafil, A., Bouzi, M., Anoune, K., & Ettalabi, N. (2020). Comparative study of forecasting methods for energy demand in Morocco. Energy Reports, 6, 523-536.

[5] Kharbach, M., & Chfadi, T. (2018). Oil prices and electricity production in Morocco. Energy strategy reviews, 22, 320-324.

[6] Ifleh, A., Bilal, A., & Kabbouri, M. E. (2022, December). Moroccan Stock Price Prediction Using Trend Technical Indicators: A Comparison Study. In International Conference on Intelligent Systems Design and Applications (pp. 380-386). Cham: Springer Nature Switzerland.

[7] Ayyadi, S., & Maaroufi, M. (2018, October). Diffusion models for predicting electric vehicles market in Morocco. In 2018 International Conference and Exposition on Electrical And Power Engineering (EPE) (pp. 0046-0051). IEEE.

[8] Adekoya, O. B., Ogunbowale, G. O., Akinseye, A. B., & Oduyemi, G. O. (2021). Improving the predictability of stock returns with global financial cycle and oil price in oil-exporting African countries. International economics, 168, 166-181.

[9] Ifleh, A., Bilal, A., & El Kabbouri, M. (2023). Comparative study of Moroccan stock price prediction with trend technical indicators. International Journal of Hybrid Intelligent Systems, (Preprint), 1-12.

[10] Benali, M., & Lahboub, K. (2024). Modelling stock prices of energy sector using supervised machine learning techniques. International Journal of Energy Economics and Policy, 14(2), 594-602.

[11] El Bahi, Y. F., Ezzine, L., Aman, Z., & El Moussami, H. (2022). DEVELOPMENT OF A NEW NUMERICAL MODEL OF DYNAMIC HARMONIC REGRESSION FOR THE FORECAST OF SELLING FUEL PRICE IN THE MOROCCAN PETROLEUM SECTOR. Acta Logistica (AL), 9(2).

[12] Lahrech, A., Alabdulwahab, S., & Chraibi, A. (2017). The impact of oil price shocks on the Moroccan financial market (from 1994 to 2010): Composite and sectorial level. International Research Journal of Finance and Economics, 164, 1450-2887.

[13] Nasreddin, D., Abdellaoui, Y., Cheracher, A., Aboutaleb, S., Benmoussa, Y., Sabbahi, I., ... & Limami, H. (2023, February). Regression and Machine Learning Modeling Comparative Analysis of Morocco's Fossil Fuel Energy Forecast. In International Conference on Artificial Intelligence & Industrial Applications (pp. 244-256). Cham: Springer Nature Switzerland.

[14] Ifleh, A., iD, A. B., & El Kabbouri, M. (2023, May). Check for updates Moroccan Stock Price Prediction Using Trend Technical Indicators: A Comparison Study. In Intelligent Systems Design and Applications: 22nd International Conference on Intelligent Systems Design and Applications (ISDA 2022) Held December 12-14, 2022-Volume 1 (Vol. 646, p. 380). Springer Nature.

[15] Siham, A. K. I. L., SEKKATE, S., & Abdellah, A. D. I. B. (2024). Exploring machine learning techniques for oil price forecasting: A comparative study of SVM, SMO, and SGD-base models. Procedia Computer Science, 232, 924-933.

[16] Itri, B., Mohamed, Y., Omar, B., Latifa, E. M., Lahcen, M., & Adil, O. (2024). Hybrid machine learning for stock price prediction in the Moroccan banking sector. International Journal of Electrical and Computer Engineering (IJECE), 14(3), 3197-3207.

[17] El Bahi, Y. F., Ezzine, L., El Moussami, H., & Aman, Z. (2018, April). Modeling and forecasting of fuel selling price using time series approach: case study. In 2018 5th International Conference on Control, Decision and Information Technologies (CoDIT) (pp. 283-288). IEEE.

[18] Bennouna, A., & El Hebil, C. (2016). Energy needs for Morocco 2030, as obtained from GDP-energy and GDP-energy intensity correlations. Energy Policy, 88, 45-55.

[19] Meliani, M., El Barkany, A., El Abbassi, I., & Mahmoudi, M. (2022). Smart grid challenges in morocco and an energy demand forecasting with time series. International Journal of Engineering Research in Africa, 61, 195-215.

[20] Zahouani, A. L., & Boubaker, H. (2023). Forecasting Crude Oil Price with Hybrid Approaches. Rev. Econ. Financ., 21, 564-576.

[21] Benabbou, F., Sael, N., & Herchy, I. (2021, March). Machine learning for used cars price prediction: Moroccan use case. In International Conference On Big Data and Internet of Things (pp. 332-346). Cham: Springer International Publishing.

[22] Ghorbel, A., Abdelhedi, M., & Boujelbene, Y. (2014). Assessing the impact of crude oil price and investor sentiment on Islamic indices: Subprime crisis. Journal of African Business, 15(1), 13-24.

[23] Dagher, L., & El Hariri, S. (2013). The impact of global oil price shocks on the Lebanese stock market. Energy, 63, 366-374.

[24] Aman, Z., Ezzine, L., El Bahi, Y. F., & EL Moussami, H. (2019). Improving the modeling and forecasting of fuel selling price using the radial basis function technique: A case study. Journal of Algorithms & Computational Technology, 13, 1748302619881120.

[25] Haouraji, C., Mounir, I., Mounir, B., & Farchi, A. (2023, October). Evolution of LPG Demand Using Machine Learning Planning Models: An Application in the Case of Morocco. In International Conference on Advanced Intelligent Systems for Sustainable Development (pp. 253-263). Cham: Springer Nature Switzerland.

[26] Abdou, H. A., Elamer, A. A., Abedin, M. Z., & Ibrahim, B. A. (2024). The impact of oil and global markets on Saudi stock market predictability: A machine learning approach. Energy Economics, 132, 107416.

[27] Oubnaki, H., Haouraji, C., Mounir, B., Mounir, I., & Farchi, A. (2022). Energy Consumption in the Transport Sector: Trends and Forecast Estimates in Morocco. In E3S Web of Conferences (Vol. 336, p. 00078). EDP Sciences.

[28] Kitous, A., Saveyn, B., Keramidas, K., Vandyck, T., Rey Los Santos, L., & Wojtowicz, K. (2016). Impact of low oil prices on oil exporting countries. JRC science for policy report.

[29] Siham, A. K. I. L., SEKKATE, S., & Abdellah, A. D. I. B. (2024). Multimodal Deep Learning for Oil Price Forecasting Using Economic Indicators. Procedia Computer Science, 236, 402-409.

[30] Bouri, E., Kachacha, I., & Roubaud, D. (2020). Oil market conditions and sovereign risk in MENA oil exporters and importers. Energy Policy, 137, 111073.

[31] Lotfi, I., & El Bouhadi, A. (2022). Artificial Intelligence methods: toward a new decision making tool. Applied Artificial Intelligence, 36(1), 1992141.

[32] Haouraji, C., Mounir, B., Mounir, I., & Farchi, A. (2020). A correlative approach, combining energy consumption, urbanization and GDP, for modeling and forecasting Morocco's residential energy consumption. International journal of energy and environmental engineering, 11(1), 163-176.

[33] Elneel, F. A., & AlMulhim, A. F. (2022). The effect of oil price shocks on Saudi Arabia's economic growth in the light of vision 2030 "A combination of VECM and ARDL models". Journal of the Knowledge Economy, 13(4), 3401-3423.

[34] Benzohra, O., Ech-Charqaouy, S. S., Fraija, F., & Saifaoui, D. (2020). Optimal renewable resources mix for low carbon production energy system in Morocco. Energy Informatics, 3, 1-21.

[35] Belcaid, K., & El Ghini, A. (2021). Macro-finance determinants and the stock market development: Evidence from Morocco. Middle East Development Journal, 13(1), 99-127.

[36] El-Karimi, M., & El-Ghini, A. (2020). The transmission of global commodity prices to consumer prices in a commodity import-dependent country: Evidence from Morocco. Scientific Annals of Economics and Business, 67(1), 15-32.

[37] El Abassi, R., Oubraime, M., Idrais, J., & Sabour, A. (2023, May). Exploring crude oil price movements as a complex time series using recurrent neural networks: Complex time series using recurrent neural networks. In Proceedings of the 6th International Conference on Networking, Intelligent Systems & Security (pp. 1-6).

[38] Vochozka, M., Janek, S., & Širáňová, L. (2023). Geopolitical deadlock and phosphate shortfall behind the price hike? Evidence from Moroccan commodity markets.

[39] Gagour, J., Oubannin, S., Bouzid, H. A., Bijla, L., El Moudden, H., Koubachi, J., ... & Gharby, S. (2022). Physicochemical characterization, kinetic parameters, shelf life and its prediction models of virgin olive oil from two cultivars ("Arbequina" and "Moroccan Picholine") grown in Morocco. OCL, 29, 39.

[40] Bounadi, I., Allali, K., Fadlaoui, A., & Dehhaoui, M. (2023). Water pollution abatement in olive oil industry in Morocco: Cost estimates and policy implications. Sustainability, 15(5), 4180.

[41] Sandeep, U., Vardhan, T. V., & Yaswanth, B. (2023, June). Cracking the Code: Unleashing the Power of Sentiment Analysis & ML for Moroccan Stock Market Forecasting. In 2023 8th International Conference on Communication and Electronics Systems (ICCES) (pp. 1274-1278). IEEE.

[42] CHIHAB, M., CHINY, M., Mabrouk, N., BOUSSATTA, H., CHIHAB, Y., & HADI, M. Y. (2022). Bilstm and multiple linear regression based sentiment analysis model using polarity and subjectivity of a text.

International Journal of Advanced Computer Science and Applications, 13(10).

[43] BOUSSATTA, H., CHIHAB, M., CHIHAB, Y., & CHINY, M. (2023). Enhancing Oil Price Forecasting Through an Intelligent Hybridized Approach. International Journal of Advanced Computer Science and Applications, 14(9).

[44] Numbeo , https://www.numbeo.com/cost-of-living/historical-prices-by-country.